

Determining the Accuracy of Maximum Likelihood Parameter Estimates With Colored Residuals

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Abstract

An important part of building high fidelity mathematical models based on measured data is calculating the accuracy associated with statistical estimates of the model parameters. Indeed, without some idea of the accuracy of parameter estimates, the estimates themselves have limited value. In this work, an expression based on theoretical analysis was developed to properly compute parameter accuracy measures for maximum likelihood estimates with colored residuals. This result is important because experience from the analysis of measured data reveals that the residuals from maximum likelihood estimation are almost always colored. The calculations involved can be appended to conventional maximum likelihood estimation algorithms. Simulated data runs were used to show that the parameter accuracy measures computed with this technique accurately reflect the quality of the parameter estimates from maximum likelihood estimation without the need for analysis of the output residuals in the frequency domain or heuristically determined multiplication factors. The result is general, although the application studied here is maximum likelihood estimation of aerodynamic model parameters from flight test data.

Nomenclature

a_z	vertical acceleration, g units
$\mathcal{D}$	dispersion matrix
$E\{ \cdot \}$	expected value
g	gravitational acceleration, 32.174 ft/sec ²
J	cost function
K_α	upwash correction
$L(\cdot)$	likelihood function
$\mathbf{M}$	information matrix
M	body axis aerodynamic pitching moment, ft-lbf
n_c	number of control vector elements
n_o	number of output vector elements
n_p	number of parameter vector elements
n_s	number of state vector elements
N	total number of sample times
$P(\cdot)$	probability distribution
q	body axis pitch rate, rad/sec
r_{ii}	i^{th} diagonal element of $\mathbf{R}$
$\mathbf{R}$	discrete noise covariance matrix
$\mathfrak{R}_{\mathbf{v}\mathbf{v}}$	autocorrelation matrix of $\mathbf{v}$
$\mathbf{S}(i)$	output sensitivity matrix at time $(i-1)\Delta t$
t	time, sec
T	data record length, sec
$\mathbf{u}(t)$	control vector
V	airspeed, ft/sec
$\mathbf{v}(i)$	output residual vector at time $(i-1)\Delta t$
$\mathbf{x}(t)$	state vector
$\mathbf{y}(t)$	output vector
$\mathbf{y}(i)$	output vector at time $(i-1)\Delta t$

$\mathbf{z}(i)$	measured output at time $(i-1)\Delta t$
Z	body axis aerodynamic vertical force, lbf
$\mathbf{Z}$	the set of N measured output vectors
α	angle of attack, rad
δ_{ij}	Kronecker delta
δ_s	stabilator deflection, rad
Δt	sample time, sec
θ	parameter vector
∇_{θ}	gradient with respect to θ
θ_j	j^{th} element of the parameter vector
σ_j	Cramer-Rao lower bound for the standard error of the j^{th} parameter
$\mathbf{v}(i)$	noise vector at time $(i-1)\Delta t$
$\mathbf{0}$	zero vector

superscripts

T	transpose
$\wedge$	estimate
$\cdot$	time derivative
-1	matrix inverse

subscripts

m	measured
o	nominal or trim value

I. Introduction

An important part of building high fidelity mathematical models for physical systems is estimating values for the model parameters based on measured data. For the case of aircraft dynamic models, these model parameters generally arise in describing the dependence of aerodynamic forces and moments on state and control variables. Of equal importance with the estimated values of the parameters is their accuracy. This accuracy can be assessed using the Cramer-Rao lower bounds¹, which represent the theoretical minimum variance that is possible for the parameter estimates using an asymptotically unbiased estimator, such as maximum likelihood. Maximum likelihood estimation is also asymptotically efficient, meaning that parameter variances computed for maximum likelihood estimates approach the Cramer-Rao bounds as the number of measured data points increases. References [1]-[3] compare and contrast the Cramer-Rao bound with other methods for assessing the accuracy of parameter estimates. The present work adopts the viewpoint of reference [3] that the Cramer-Rao bound is the best accuracy measure for maximum likelihood parameter estimates.

In this work, the output error formulation of maximum likelihood parameter estimation was used with a fixed linear model structure. This formulation includes measurement noise, but no process noise⁴. The optimization procedure used to determine the maximum likelihood parameter estimates was modified Newton-Raphson^{4,5}. In this case, the Cramer-Rao bounds are computed as part of the estimation procedure. It is well known, however, that the Cramer-Rao bounds computed in this way are usually optimistic (too small) compared to the scatter in the parameter estimates from repeated flight test maneuvers^{3,6}. This prompted the work of Maine, Iliff and Balakrishnan^{3,4,7-9} who traced the discrepancy to the fact that the residuals are colored for real flight test data analysis because output error techniques lump the (unavoidable) deterministic modelling error together with the incoherent part of a measured signal and call this the measurement noise³. This results in the measurement noise being colored, because the modeling error generally lies roughly in the same frequency band as the aircraft rigid body dynamics and accounts for a large part of the total noise power. Colored measurement noise impacts parameter estimate accuracy measures, as detailed in references [3],[4],[7]-[9].

The theory underlying the output error formulation of maximum likelihood estimation assumes that the measurement noise is white Gaussian and band limited by the Nyquist frequency. The band limit is the result of discrete measurements taken at the sampling frequency, which is twice the Nyquist frequency. This measurement noise is broad band and incoherent. The term incoherent is meant to imply amplitude discontinuity and a lack of consistent phase-amplitude relationships, causing the autocorrelation function to be close to the impulse function. Heuristically, this part of the residual would be commonly recognized as having no deterministic component. If the structure of the model were correct, the residuals could be expected to be reasonably close to this type of noise. In real flight test data analysis, the

residuals inevitably contain deterministic components from such sources as approximations of real aircraft aerodynamic dependencies, unmodeled dynamics such as structural modes, and linearization of the nonlinear equations of motion. References [3], [4], [7]-[9] point out that colored residuals violate the assumptions of conventional maximum likelihood theory and lead to the aforementioned inaccuracy in the Cramer-Rao bounds.

In reference [3], several engineering solutions were proposed to correct for the discrepancy. Each of these solutions was based on the fact that most of the residual power for real flight data analysis is concentrated at relatively low frequencies and is due to deterministic modeling error. This assumption is stretched when relatively high frequency structural modes appear in the data or when the broad band random noise has a large enough magnitude to rival the power of the band limited noise due to modeling error. The solutions offered in reference [3] depend on knowing something about the bandwidth of the dominant source of power in the residuals. Obtaining this information requires Fourier transforms of the residuals and analysis in the frequency domain. The spectra of the residuals depend on the model, the flight condition, the maneuver, and the instrumentation characteristics. All of these factors may change over the course of a flight test program, requiring changes in the corrections for the Cramer-Rao bounds. Finally, all the solutions offered in reference [3] require some engineering judgment, which requires an experienced analyst and limits the quantitative accuracy of the results.

In the present work, a technique was developed which processes the residuals of a conventional maximum likelihood estimation in order to compute quantitatively accurate Cramer-Rao lower bounds for arbitrary residuals. The approach accounts for colored residuals using a simple estimate of the residual correlation. Cramer-Rao lower bounds for the maximum likelihood estimates can be determined automatically and accurately with no heuristic multiplication factors. In addition, existing maximum likelihood estimation routines can be easily upgraded because the technique can be considered a post-processing of the output residuals in order to compute the appropriate Cramer-Rao lower bounds.

The next section contains the theoretical analysis. Following this, the technique was applied in a controlled situation using simulated data. A model of the longitudinal dynamics of a fighter aircraft was used with the true parameter values known. The simulated outputs were corrupted by discrete white Gaussian noise with zero mean. Using ten simulation runs with different realizations of the noise process, it was shown that both the conventional method for computing Cramer-Rao lower bounds and the new technique described in this work produced Cramer-Rao lower bounds representative of the observed scatter in the parameter estimates. Implementation of the new technique was in a subroutine which post-processed the output residuals from the conventional maximum likelihood estimation. Next, the same simulated outputs were corrupted with band limited white noise produced by passing zero mean discrete white Gaussian noise through an 0.5 hz low pass filter and scaling the amplitudes to maintain the same signal to noise

ratio used for the wide band noise cases. Ten different noise sequences were used. In these cases, the Cramer-Rao bounds computed using the conventional method produced optimistic values of the Cramer-Rao lower bounds, in agreement with the results of previous research^{3,4,6-9}. The new technique, however, successfully accounted for the band limited residuals and produced quantitatively correct values for the Cramer-Rao lower bounds. Finally, ten different colored noise sequences comprised of a mixture of band limited and wide band noise sequences were generated, again scaling the amplitudes to maintain signal to noise ratio. These colored noise sequences were very similar to residuals observed when analyzing real flight test data. Again, the conventional method gave optimistic Cramer-Rao lower bounds while the new technique produced Cramer-Rao bounds which accurately characterized the scatter in the parameter estimates. This analysis lends confidence in the new technique for future application to determining appropriate Cramer-Rao lower bounds for parameters estimated from flight test data.

II. Theoretical Development

A linear model structure for the aircraft dynamics was assumed *a priori* as a result of the small perturbations assumption. The control inputs were considered perturbations about trim. The model can be represented as

$$\dot{\mathbf{x}}(t) = \mathbf{A}(\theta)\mathbf{x}(t) + \mathbf{B}(\theta)\mathbf{u}(t) \quad (1)$$

$$\mathbf{x}(0) = \mathbf{0} \quad (2)$$

$$\mathbf{y}(t) = \mathbf{C}(\theta)\mathbf{x}(t) + \mathbf{D}(\theta)\mathbf{u}(t) \quad (3)$$

$$\mathbf{z}(i) = \mathbf{y}(i) + \mathbf{v}(i) \quad i = 1, 2, \dots, N \quad (4)$$

where $\mathbf{x}$ is the $n_s \times 1$ state vector, $\mathbf{u}$ is the $n_c \times 1$ control vector, and $\mathbf{y}$ is the $n_o \times 1$ output vector. The $n_o \times 1$ measured output vector is represented by $\mathbf{z}(i)$. The notation $\mathbf{y}(i)$ represents the sampled value of $\mathbf{y}(t)$ at $t=(i-1)\Delta t$. There are N sampled data points. For conventional maximum likelihood, the discrete measurement noise vector $\mathbf{v}(i)$ is assumed to be zero mean white Gaussian and band limited at the Nyquist frequency with

$$E\{\mathbf{v}(i)\} = \mathbf{0} \quad E\{\mathbf{v}(i)\mathbf{v}^T(j)\} = \mathbf{R} \delta_{ij} \quad (5)$$

where $\mathbf{R}$ is the discrete noise covariance matrix, δ_{ij} is the Kronecker delta, and E is the expectation operator.

The maximum likelihood estimate of the parameter vector maximizes the conditional probability of realizing the measurements^{4,5}:

$$\hat{\theta} = \arg \max_{\theta} [P(\mathbf{Z} | \theta)] \quad (6)$$

where $\mathbf{Z}$ is the set of all measurement vectors, $\mathbf{z}(i)$ for $i=1, 2, \dots, N$. The conditional probability distribution, $P(\mathbf{Z} | \theta)$, is also known as the likelihood function, $L(\theta)$, and is given by

$$L(\theta) \equiv P(\mathbf{Z} | \theta) = \frac{1}{[(2\pi)^{n_o} |\mathbf{R}|]^{N/2}} \exp \left\{ -\frac{1}{2} \sum_{i=1}^N [\mathbf{z}(i) - \mathbf{y}(i)]^T \mathbf{R}^{-1} [\mathbf{z}(i) - \mathbf{y}(i)] \right\} \quad (7)$$

Maximizing the likelihood function in equation (7) is equivalent to minimizing its negative logarithm, known as the log likelihood function,

$$-\ln L(\theta) = \frac{1}{2} \sum_{i=1}^N [\mathbf{z}(i) - \mathbf{y}(i)]^T \mathbf{R}^{-1} [\mathbf{z}(i) - \mathbf{y}(i)] + \frac{N}{2} \ln |\mathbf{R}| \quad (8)$$

where the added constant $\frac{n_o N}{2} \ln(2\pi)$ was omitted because it has no effect on the optimization.

When $\mathbf{R}$ is known, minimizing the log likelihood function in equation (8) is equivalent to minimizing the cost function

$$J(\theta) = \frac{1}{2} \sum_{i=1}^N [\mathbf{z}(i) - \mathbf{y}(i)]^T \mathbf{R}^{-1} [\mathbf{z}(i) - \mathbf{y}(i)] \quad (9)$$

The cost in equation (9) can be minimized using a modified Newton-Raphson technique to determine parameter updates⁵, starting from some initial guess of the parameter vector. The initial guess for the parameter vector can be obtained from equation error methods⁶. When the parameter vector estimate, $\hat{\theta}$, is close to the true parameter vector, θ , the estimated output can be linearized with respect to the parameter vector,

$$\mathbf{y}(i) = \hat{\mathbf{y}}(i) + \left. \frac{\partial \mathbf{y}(i)}{\partial \theta} \right|_{\theta=\hat{\theta}} (\theta - \hat{\theta}) \quad i = 1, 2, \dots, N \quad (10)$$

where $\hat{\mathbf{y}}(i)$ denotes the output vector computed using the estimated parameter vector $\hat{\theta}$ at time $(i-1)\Delta t$. Defining the sensitivity matrix,

$$\mathbf{S}(i) = \left. \frac{\partial \mathbf{y}(i)}{\partial \theta} \right|_{\theta=\hat{\theta}} \quad i = 1, 2, \dots, N \quad (11)$$

equation (10) becomes

$$\mathbf{y}(i) = \hat{\mathbf{y}}(i) + \mathbf{S}(i)(\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}) \quad i = 1, 2, \dots, N \quad (12)$$

The j^{th} column of the sensitivity matrix contains the output sensitivities for the j^{th} parameter, θ_j , computed from

$$\frac{d}{dt} \left[\frac{d\mathbf{x}}{d\theta_j} \right] = \frac{d\mathbf{A}}{d\theta_j} \mathbf{x} + \mathbf{A} \frac{d\mathbf{x}}{d\theta_j} + \frac{d\mathbf{B}}{d\theta_j} \mathbf{u} \quad (13)$$

$$\frac{d\mathbf{x}}{d\theta_j}(0) = \mathbf{0} \quad (14)$$

$$\frac{d\mathbf{y}}{d\theta_j} = \frac{d\mathbf{C}}{d\theta_j} \mathbf{x} + \mathbf{C} \frac{d\mathbf{x}}{d\theta_j} + \frac{d\mathbf{D}}{d\theta_j} \mathbf{u} \quad (15)$$

for $j=1, 2, \dots, n_p$, where n_p is the number of parameters. Equations (13)-(15) follow from differentiating equations (1)-(3) with respect to the θ_j , along with the assumed analyticity of $\mathbf{x}$.

To minimize the cost function, substitute for $\mathbf{y}(i)$ from equation (12) into equation (9) and set the gradient of the cost function with respect to the parameter vector equal to zero,

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = - \sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \left[\mathbf{z}(i) - \hat{\mathbf{y}}(i) - \mathbf{S}(i)(\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}) \right] = \mathbf{0} \quad (16)$$

Solving for the parameter update gives

$$\Delta \hat{\boldsymbol{\theta}} \equiv \boldsymbol{\theta} - \hat{\boldsymbol{\theta}} = \left[\sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \mathbf{S}(i) \right]^{-1} \sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} [\mathbf{z}(i) - \hat{\mathbf{y}}(i)] \quad (17)$$

Equation (17) gives the modified Newton-Raphson step which is added to a current estimate of the parameter vector in order to approach the true value of the parameter vector. The "modified Newton-Raphson" name arises from the fact that equation (17) can also be found by expanding the cost function to second order in terms of $\Delta\hat{\theta}$, and using a conventional Newton-Raphson optimization with part of the second order gradient term dropped (see reference [5] for details). In practice, there are times when the modified Newton-Raphson step computed from equation (17) leads to an increase in the cost function or a divergence. This is because the Newton-Raphson step assumes that the current estimate of the parameter vector is near the true value. Using several iterations of a simplex algorithm¹⁰ when the Newton-Raphson step produces an increase in the cost was found to be very effective. This approach was followed in the present study and makes the optimization divergence proof. If measured outputs are used instead of computed outputs to force the sensitivity equations in the first calculation of the modified Newton-Raphson step (see reference [5] for details), the solution of the maximum likelihood estimation problem becomes insensitive to initial parameter estimates and it is not necessary to use equation error methods to determine good starting values for the parameters. This technique was used for all maximum likelihood estimation in the present work.

When repeated application of equation (17) converges, an estimate of the measurement noise covariance matrix, $\mathbf{R}$, can be obtained from the output residuals. The expression for the estimate of $\mathbf{R}$ comes from taking the derivative of the right hand side of equation (8) with respect to $\mathbf{R}$, setting the result equal to zero, and solving for $\mathbf{R}$,

$$\hat{\mathbf{R}} = \frac{1}{N} \sum_{i=1}^N [\mathbf{z}(i) - \mathbf{y}(i)][\mathbf{z}(i) - \mathbf{y}(i)]^T \quad (18)$$

Often only the diagonal elements of the $\mathbf{R}$ matrix are estimated from equation (18), enforcing an assumption that the measurement noise sequences for the n_o measured outputs are uncorrelated with one another. This assumption is generally a good one for real flight test data. All estimates of the measurement noise covariance matrix in this work assume a diagonal $\hat{\mathbf{R}}$ matrix. Retaining the full $\hat{\mathbf{R}}$ matrix could have been done with little conceptual difficulty, but the expected gains did not warrant the extra computation involved. The noise covariance matrix estimate, $\hat{\mathbf{R}}$, was used in the cost function of equation (9), and the minimization process described above for known $\mathbf{R}$ was repeated. Thus, the maximum likelihood estimation proceeds by alternately estimating the noise covariance matrix from equation (18) and minimizing the cost function using equation (17) with the latest value of the estimated noise covariance matrix. Convergence is reached when the estimated parameter vector, $\hat{\theta}$, the estimated noise covariance matrix, $\hat{\mathbf{R}}$, and the cost, $J(\hat{\theta})$, reach nearly constant values. Since maximum likelihood

estimation is asymptotically unbiased⁴, the estimated parameter vector, $\hat{\theta}$, should be close to the true value, θ , and the gradient of the cost function with respect to the parameter vector should be close to zero. From equation (16),

$$\nabla_{\theta} J(\theta)|_{\theta=\hat{\theta}} \approx -\sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} [\mathbf{z}(i) - \hat{\mathbf{y}}(i)] \approx \mathbf{0} \quad (19)$$

For practical computation, simultaneous satisfaction of the numerical criteria given below were used to define convergence of the maximum likelihood estimation:

$$\begin{aligned} \left| [\hat{\theta}_j]_k - [\hat{\theta}_j]_{k-1} \right| &< 1.0 \times 10^{-5} \quad \forall j, \quad j = 1, 2, \dots, n_p \\ \left| \frac{[\hat{r}_{ii}]_k - [\hat{r}_{ii}]_{k-1}}{[\hat{r}_{ii}]_{k-1}} \right| &< 0.05 \quad \forall i, \quad i = 1, 2, \dots, n_o \\ \left| \frac{J(\hat{\theta}_k) - J(\hat{\theta}_{k-1})}{J(\hat{\theta}_{k-1})} \right| &< 0.001 \\ \left| \frac{\partial J(\theta)}{\partial \theta_j} \right|_{\theta=\hat{\theta}} &< 0.05 \quad \forall j, \quad j = 1, 2, \dots, n_p \end{aligned} \quad (20)$$

where k denotes the current estimate iteration number and $\hat{r}_{ii}$ denotes the estimate of the i^{th} diagonal element of the discrete measurement noise covariance matrix. The approximate expression for the cost gradient with respect to the parameters (equation (19)) was used for the last criterion in (20).

The minimum achievable parameter variances using an asymptotically unbiased and efficient estimator, such as maximum likelihood, are called the Cramer-Rao lower bounds and are given by the diagonal elements of the dispersion matrix, $\mathcal{D}$ ³⁻⁵. This dispersion matrix is defined as the inverse of the information matrix $\mathbf{M}$, the latter being a measure of the information contained in the data from an experiment. The expressions for these matrices are^{3,4}

$$\mathbf{M} = \sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \mathbf{S}(i) \quad (21)$$

$$\mathcal{D} = \mathbf{M}^{-1} = \left[\sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \mathbf{S}(i) \right]^{-1} \quad (22)$$

The square root of the j^{th} diagonal element of $\mathcal{D}$, d_{jj} , gives the Cramer-Rao lower bound for the standard error of the j^{th} parameter,

$$\sigma_j = \sqrt{d_{jj}} \quad j = 1, 2, \dots, n_p \quad (23)$$

It can be seen from equations (17) and (22) that the dispersion matrix is computed when determining the modified Newton-Raphson step as part of the conventional maximum likelihood estimation. The assumption that the output residuals are white and therefore uncorrelated in time is implicit in the algorithm and indicated in equation (5). The next section details the theory involved in accounting for arbitrary colored output residuals, which are correlated in time.

When the conventional maximum likelihood estimation has converged, the estimated parameter vector will be close to the true value and equation (17) holds. Define the residual vector

$$\mathbf{v}(i) \equiv \mathbf{z}(i) - \hat{\mathbf{y}}(i) \quad i = 1, 2, \dots, N \quad (24)$$

The estimated parameter covariance matrix can be expressed using equation (17) with substitutions from the definitions in equations (22) and (24),

$$E\left\{(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})^T\right\} = E\left\{\sum_{i=1}^N \sum_{j=1}^N \mathcal{D} \mathbf{S}(i)^T \mathbf{R}^{-1} \mathbf{v}(i) \mathbf{v}(j)^T \mathbf{R}^{-1} \mathbf{S}(j) \mathcal{D}\right\} \quad (25)$$

The dispersion matrix, the discrete noise covariance matrix inverse and the sensitivities in equation (25) are from the conventional maximum likelihood estimation. If it is assumed that the dependence of these quantities on the parameter vector estimate is small at the maximum likelihood solution, the estimated parameter covariance matrix can be written as

$$E\left\{\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)^T\right\} = \mathcal{D} \left[\sum_{i=1}^N \sum_{j=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} E\{\mathbf{v}(i)\mathbf{v}(j)^T\} \mathbf{R}^{-1} \mathbf{S}(j) \right] \mathcal{D} \quad (26)$$

When the output residuals are assumed to be zero mean white (see equation (5)), then

$$E\{\mathbf{v}(i)\mathbf{v}(j)^T\} = \mathbf{R} \delta_{ij} \quad (27)$$

From equations (22), (26) and (27) it is easy to see that the parameter vector covariance matrix reduces to the dispersion matrix, $\mathcal{D}$, when the output residuals are white. For colored residuals, the estimated parameter covariance matrix can be computed from equation (26) using an estimated value for $E\{\mathbf{v}(i)\mathbf{v}(j)^T\}$. Define the discrete autocorrelation of the output residuals,

$$\mathfrak{R}_{\mathbf{vv}}(k) \equiv \frac{1}{N} \sum_{i=1}^N \mathbf{v}(i)\mathbf{v}(i+k)^T = \mathfrak{R}_{\mathbf{vv}}(-k) \quad (28)$$

where $\mathbf{v}$ is assumed to be periodic, so that $\mathbf{v}(N+1)=\mathbf{v}(1)$, $\mathbf{v}(N+2)=\mathbf{v}(2)$, etc. It follows that

$$E\{\mathbf{v}(i)\mathbf{v}(j)^T\} = \mathfrak{R}_{\mathbf{vv}}(i-j) \quad (29)$$

Substituting equation (29) into equation (26),

$$E\left\{\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)^T\right\} = \mathcal{D} \left[\sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \sum_{j=1}^N \mathfrak{R}_{\mathbf{vv}}(i-j) \mathbf{R}^{-1} \mathbf{S}(j) \right] \mathcal{D} \quad (30)$$

Setting $k = i - j$, equation (30) can be written as

$$E\left\{\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)\left(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right)^T\right\} = \mathcal{D} \left[\sum_{i=1}^N \mathbf{S}(i)^T \mathbf{R}^{-1} \left(\sum_{k=i-N}^{i-1} \mathfrak{R}_{\mathbf{vv}}(k) \mathbf{R}^{-1} \mathbf{S}(i-k) \right) \right] \mathcal{D} \quad (31)$$

Equation (31) was used to account for colored residuals, which are correlated in time. The dispersion matrix, $\mathcal{D}$, the estimated noise covariance matrix inverse, $\mathbf{R}^{-1}$, and the sensitivities, $\mathbf{S}$, are from the conventional maximum likelihood estimation. Equations (28) and (31) embody the required post-processing applied to a conventional maximum likelihood solution to account for colored residuals.

For unbiased parameter estimates, the Cramer-Rao inequality can be stated in general form as

$$E\left\{\left(\hat{\theta} - \theta\right)\left(\hat{\theta} - \theta\right)^T\right\} \geq \left[-E\left\{\nabla_{\theta}^2 \ln P(\mathbf{Z}|\theta)\right\}\right]^{-1} \quad (32)$$

When the discrete measurement noise is white out to the Nyquist frequency with known covariance, substituting for $P(\mathbf{Z}|\theta)$ from equation (7) makes the right side of inequality (32) equal to the dispersion matrix (cf. equation (22)).

If the colored noise sequence representing the residuals is assumed to be caused by modeling error, then the maximum likelihood parameter estimates are biased, so that

$$E\{\hat{\theta}\} = \theta + \mathbf{b}(\theta) \quad (33)$$

where $\mathbf{b}(\theta)$ is a vector of bias errors which are unknown and unknowable in practice. For the biased parameter estimates, the right side of inequality (32) will include additional terms where the elements of the dispersion matrix will be multiplied by $\nabla_{\theta} \mathbf{b}(\theta)$ and $[\nabla_{\theta} \mathbf{b}(\theta)][\nabla_{\theta} \mathbf{b}(\theta)]^T$ (see reference [3] for details). In the present analysis, the deterministic modeling error is included in the measurement noise, making the residuals colored. The approach taken here for arbitrary frequency content in the measurement noise could then be viewed as effectively including the bias error due to deterministic modeling error as part of the parameter accuracy measure which accounts for colored residuals.

IV. Results

The longitudinal short period dynamics of the F-18 High Angle of Attack Research Vehicle (HARV) fighter aircraft at approximately 20 degrees angle of attack and an altitude of 25,000 feet were simulated for this study. The model was

$$\begin{bmatrix} \dot{\alpha}(t) \\ \dot{q}(t) \end{bmatrix} = \begin{bmatrix} Z_{\alpha} & 1 + Z_q \\ M_{\alpha} & M_q \end{bmatrix} \begin{bmatrix} \alpha(t) \\ q(t) \end{bmatrix} + \begin{bmatrix} Z_{\delta_s} & Z_o \\ M_{\delta_s} & M_o \end{bmatrix} \begin{bmatrix} \delta_s(t) \\ 1 \end{bmatrix} \quad (34)$$

$$\begin{bmatrix} \alpha(0) \\ q(0) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (35)$$

$$\begin{bmatrix} \alpha_c(t) \\ q(t) \\ a_z(t) \end{bmatrix} = \begin{bmatrix} K_{\alpha} & 0 \\ 0 & 1 \\ \frac{V_o Z_{\alpha}}{g} & \frac{V_o Z_q}{g} \end{bmatrix} \begin{bmatrix} \alpha(t) \\ q(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \frac{V_o Z_{\delta_s}}{g} & a_{z_o} \end{bmatrix} \begin{bmatrix} \delta_s(t) \\ 1 \end{bmatrix} \quad (36)$$

$$\begin{bmatrix} \alpha_m(i) \\ q_m(i) \\ a_{z_m}(i) \end{bmatrix} = \begin{bmatrix} \alpha_c(i) \\ q(i) \\ a_z(i) \end{bmatrix} + \begin{bmatrix} v_1(i) \\ v_2(i) \\ v_3(i) \end{bmatrix} \quad (37)$$

The input was symmetric stabilator deflection in radians (δ_s), and the measured output quantities were angle of attack in radians (α_m), pitch rate in radians per second (q_m), and vertical acceleration in g units (a_{z_m}).

To assess the performance of the new technique for computing Cramer-Rao bounds, thirty simulation runs were made using various measurement noise processes. Maximum likelihood estimation as described in the previous section was used to estimate the parameters. Since the true parameter values were known for the simulation data, the true accuracy of the maximum likelihood estimates could be compared to that indicated by the conventional calculation of the Cramer-Rao bounds (equations (18) and (22)) and the alternate calculation accounting for arbitrary frequency content in the residuals (equation (31)).

To make the simulation runs realistic, the stabilator input was taken from measured data for the F-18 HARV flying a maneuver designed specifically for accurate parameter estimation¹¹. The stabilator input is shown in figure 1. In addition, the true values of the parameters (given in column 2 of Table 1) approximately reflect the short period dynamics of the F-18 HARV at 20 degrees angle of attack and an altitude of 25,000 feet. The stabilator input and true parameter values were the same for each simulated data run, so that the information in the data was constant. The sampling rate was 50 hz and the time length was 14 seconds. Standard errors from the Cramer-Rao bounds computed using the conventional computation come from the square root of the diagonal elements of matrix $\mathcal{D}$ in equation (22), with $\mathbf{R}$ estimated from equation (18). The standard errors based on the Cramer-Rao bounds corrected for colored residuals are the square root of the diagonal elements of the matrix computed by equation (31). Results from both the conventional computation and the corrected calculation were expressed in terms of the ratio of the absolute deviation of each parameter estimate from its true value to the computed standard error from the Cramer-Rao bound, $|\hat{\theta}_j - \theta_j|/\sigma_j$, for $j=1,2,\dots,n_p$. For any given maneuver, only the denominator of this ratio was different for the conventional versus corrected calculations of the Cramer-Rao bounds. For a maximum likelihood estimator, the probability distribution of the parameter estimates about their true value approaches a Gaussian distribution as the number of data points gets large. Therefore, these ratios should be less than 3 almost all the time if the computed Cramer-Rao bounds reflect the true accuracy of the estimates.

For the first ten simulation runs, the added measurement noise was zero mean white Gaussian, with standard deviations set to one fifth the root mean square of each uncorrupted output. This made all signal to noise ratios approximately 5 to 1. Typical simulated measured outputs are shown in figure 2, from run 1. Figure 3 shows a typical noise sequence. Noise power was uniform over the entire frequency band out to the Nyquist frequency, 25 hz, as shown in the noise power spectrum of figure 4.

Tables 1 through 10 contain the results from the maximum likelihood estimation using simulated data runs 1 through 10, respectively. The values in the last two columns of each table are the ratio of true parameter estimate accuracy to the computed Cramer-Rao bounds for the standard errors. Measurement noise power was evenly distributed up to the Nyquist frequency for each of these cases. Nearly all values in the last two columns of tables 1 through 10 were less than 3, indicating that both the conventional and the corrected Cramer-Rao bounds accurately reflected the true parameter estimation accuracy. Figures 5 and 6 depict typical results for one parameter, Z_α , for these 10 runs. The error bars represent the Cramer-Rao bounds for the standard errors computed using the conventional calculation for figure 5 and the corrected calculation for figure 6. The error bars in both plots accurately reflect the scatter of the parameter estimates. The harmony between the Cramer-Rao bounds and the scatter in the estimates indicates that there is sufficient information in the data and that the length of the data records is

sufficient for the true accuracy of the parameter estimates to closely approach the Cramer-Rao bounds.

For simulation runs 11 through 20, the random measurement noise power was limited to frequencies between 0 hz and 0.5 hz, inclusive. This frequency band corresponds roughly to the bandwidth of the uncorrupted simulated outputs. Figure 7 shows typical simulated measured outputs which have been corrupted by the band limited noise, from run 11. The noise sequence was generated by passing zero mean white Gaussian noise through a fifth order Chebyshev low pass filter with frequency cutoff set at 0.5 hz, then scaling the resulting band limited noise to achieve the same 5 to 1 signal to noise ratio used for the other simulation runs. Figure 8 shows a typical band limited noise sequence. Figure 9 is the corresponding power spectrum, showing essentially no components above 0.5 hz.

Tables 11 through 20 contain the results from the maximum likelihood estimation using the simulated data runs 11 through 20, respectively. The data in these tables show that the conventional calculation for the Cramer-Rao bounds frequently gave values that were too small (see the fourth column of each table). In contrast, the last column of each table indicates that the corrected calculation for the Cramer-Rao bounds has properly accounted for the change in the residual spectra, since these values rarely exceed 3.

Figures 10 and 11 depict the results for one parameter, Z_{α} , for these 10 runs. The error bars represent the Cramer-Rao bounds for the standard errors computed using the conventional calculation for figure 10 and the corrected calculation for figure 11. These plots show that the standard calculation for the Cramer-Rao bounds gave optimistic values, whereas the corrected calculation for the Cramer-Rao bounds automatically produced Cramer-Rao bounds which accurately reflect the scatter of the estimates. Results for other parameters were similar to those plotted in figures 10 and 11 for Z_{α} .

It was not necessary to supply information about the bandwidth of the dominant power in the residuals to the algorithm for corrected Cramer-Rao bounds because this information was incorporated automatically via the autocorrelation function appearing in equation (31). Thus, the algorithm should work for arbitrary residual spectra. This attribute can be important when the colored measurement noise includes significant power from unmodeled structural modes, whose frequency content is generally higher than that of the rigid body dynamics.

For simulation runs 21 through 30, ten different colored noise sequences were used with the same uncorrupted simulation outputs. Each noise sequence had 90% of its power in the frequencies between 0 hz and 0.5 hz inclusive, with the remaining power taken by white Gaussian noise out to the Nyquist frequency. The noise sequences were thus a combination of the two types of noise used previously. Figure 12 shows typical simulated measured outputs which have been corrupted by the colored noise, from run 21. This type of noise is quite close to the residual sequences observed when analyzing real flight test data, and was chosen for that

reason. The band limited part of the noise sequence was generated in the same manner as before, and the resulting colored noise sequences were scaled to maintain the same 5 to 1 signal to noise ratio used in the other simulation runs. Figure 13 shows a typical colored noise sequence. Figure 14 is the colored noise power spectrum, showing most of the power below 0.5 hz, with some small components out to the Nyquist frequency, 25 hz. The vertical scale for figure 14 is logarithmic so that the relatively small high frequency components can be seen.

Tables 21 through 30 contain the results from the maximum likelihood estimation using the simulated data runs 21 through 30, respectively. As in the case of narrow band limited noise, the data in these tables show that the conventional calculation for the Cramer-Rao bounds frequently gave optimistic values for the parameter accuracies. The last column of each table indicates that the corrected calculation for the Cramer-Rao bounds again properly accounted for the change in the residual spectra. As before, the values in the last column of each table rarely exceed 3. Additional runs (results not shown) were made with various residual power spectra, including some runs where residuals from flight test data analysis were added to the uncorrupted simulated outputs. Results from all these cases were very similar to those presented in tables 11-30.

Figures 15 and 16 depict the results for one parameter, Z_{α} , for the 10 colored noise runs. The error bars represent the Cramer-Rao bounds for the standard errors computed using the conventional calculation for figure 15 and the corrected calculation for figure 16. Results for other parameters were similar to those plotted in figures 15 and 16. From these plots, and in general from the last two columns of tables 11-30, it is clear that the conventional calculation for the Cramer-Rao bounds gave optimistic values for the Cramer-Rao bounds when the residual spectrum was not white out to the Nyquist frequency. This is in agreement with previous research^{3,4,8,9}. In addition, the extent to which the conventional Cramer-Rao bounds misrepresented the true parameter accuracy was neither consistent nor predictable from parameter to parameter or from run to run. This phenomena has been observed previously when analyzing flight test data from repeated maneuvers⁶. It follows that the common practice of applying a fixed correction factor to the conventional calculation of the Cramer-Rao bounds is incorrect to a varying and unpredictable degree in cases where the residual spectrum is colored by modeling error in the frequency band of the system dynamics. The corrected calculation for the Cramer-Rao bounds presented here produced consistently accurate measures of the scatter in the parameter estimates, using an algorithm with moderate computational cost that can be applied as a post-processing of the output residuals from a conventional maximum likelihood solution.

V. Concluding Remarks

Algorithms for aircraft parameter estimation using the output error formulation of maximum likelihood are in widespread use. Current practice for determining the accuracy of such estimates calls for use of a correction factor to account for the fact that the output residuals from real flight test data analysis are virtually never white out to the Nyquist frequency, as assumed in the conventional theory, but rather are colored, with most of the power in a frequency band similar to that of the system dynamics. Such an approach is shown here to be inadequate if a quantitative measure of the accuracy of the parameter estimates is desired. In this work, an expression based on theoretical analysis was developed to compute parameter accuracy measures for maximum likelihood estimates with colored residuals. This result is important because the residuals from maximum likelihood estimation are almost always colored in practice, due to unmodeled dynamics in the real physical system. At a more general level, the utility of the parameter estimates is limited when there is no firm idea of the accuracy of the estimates.

The calculations involved in the algorithm for computing Cramer-Rao bounds that account for colored residuals can be carried out in a short subroutine called at the conclusion of a conventional maximum likelihood estimation algorithm. This approach was used to generate the results in this report. Bandwidth of the dominant power in the residuals need not be known or estimated, as it is accounted for automatically in the algorithm. In addition, there is no need for heuristic correction factors. The algorithm works for arbitrary residual spectra and all calculations are performed in the time domain. This obviates the need for any frequency domain analysis of the residuals.

Simulated data runs using various noise sequences were carried out to demonstrate the performance of the algorithm in computing the Cramer-Rao bounds. This analysis showed that the algorithm developed in this work is a simple, accurate, and generally applicable technique for quantitative determination of the quality of parameter estimates for the output error formulation of maximum likelihood estimation.

VI. Acknowledgments

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Table 1 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 1 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1177	1.0548	1.4207
Z_q	-0.0600	-0.0611	0.7296	1.2435
$Z_{\delta s}$	-0.0496	-0.0504	0.4106	0.4040
Z_o	0.0000	0.0001	0.5446	0.5244
M_{α}	-0.6600	-0.6539	0.7539	0.9211
M_q	-0.1400	-0.1447	0.7933	1.1264
$M_{\delta s}$	-1.3265	-1.3405	1.0528	1.4058
M_o	0.0000	-0.0003	1.0208	1.4282
K_{α}	1.0000	0.9816	1.5406	2.5668
a_{z_o}	0.0000	-0.0007	0.9368	1.5153

Table 2 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 2 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1209	0.4131	0.3967
Z_q	-0.0600	-0.0585	1.0211	1.0842
$Z_{\delta s}$	-0.0496	-0.0541	2.5239	2.0164
Z_o	0.0000	0.0000	0.0664	0.1083
M_{α}	-0.6600	-0.6636	0.4567	0.4623
M_q	-0.1400	-0.1500	1.6872	1.6888
$M_{\delta s}$	-1.3265	-1.3275	0.0767	0.0677
M_o	0.0000	0.0001	0.2690	0.3230
K_{α}	1.0000	1.0144	1.1990	1.0913
a_{z_o}	0.0000	-0.0001	0.1342	0.1777

Table 3 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 3 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1221	0.9816	1.4478
Z_q	-0.0600	-0.0585	1.0225	2.1056
$Z_{\delta s}$	-0.0496	-0.0490	0.3159	0.4469
Z_o	0.0000	0.0001	0.4658	0.9001
M_α	-0.6600	-0.6673	0.9080	0.9536
M_q	-0.1400	-0.1361	0.6594	0.9567
$M_{\delta s}$	-1.3265	-1.3218	0.3490	0.4327
M_o	0.0000	-0.0003	1.0256	1.2033
K_α	1.0000	0.9993	0.0597	0.0993
a_{z_o}	0.0000	-0.0006	0.8730	1.4775

Table 4 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 4 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1202	0.0841	0.0959
Z_q	-0.0600	-0.0585	1.0499	1.8280
$Z_{\delta s}$	-0.0496	-0.0484	0.6696	0.6834
Z_o	0.0000	0.0000	0.0428	0.0442
M_α	-0.6600	-0.6619	0.2438	0.2520
M_q	-0.1400	-0.1356	0.7730	1.1375
$M_{\delta s}$	-1.3265	-1.3294	0.2257	0.2718
M_o	0.0000	-0.0002	0.6695	0.7191
K_α	1.0000	0.9872	1.0725	1.4470
a_{z_o}	0.0000	-0.0002	0.3259	0.4406

Table 5 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 5 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1227	1.2756	1.6603
Z_q	-0.0600	-0.0592	0.5819	0.7766
$Z_{\delta s}$	-0.0496	-0.0471	1.4643	1.6532
Z_o	0.0000	0.0001	0.5712	0.8265
M_{α}	-0.6600	-0.6638	0.4640	0.6219
M_q	-0.1400	-0.1410	0.1600	0.1766
$M_{\delta s}$	-1.3265	-1.3114	1.1265	1.2809
M_o	0.0000	-0.0003	1.0805	1.5154
K_{α}	1.0000	1.0137	1.0843	1.4075
a_{z_o}	0.0000	-0.0010	1.3312	2.2710

Table 6 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 6 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1221	0.9482	1.4726
Z_q	-0.0600	-0.0607	0.4725	0.8838
$Z_{\delta s}$	-0.0496	-0.0509	0.6952	0.8868
Z_o	0.0000	0.0000	0.1016	0.2306
M_{α}	-0.6600	-0.6714	1.3503	1.7707
M_q	-0.1400	-0.1421	0.3458	0.5127
$M_{\delta s}$	-1.3265	-1.2985	2.0312	2.8107
M_o	0.0000	-0.0003	0.8904	1.3496
K_{α}	1.0000	1.0071	0.5587	0.9856
a_{z_o}	0.0000	0.0004	0.5209	1.0113

Table 7 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 7 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1230	1.3563	1.8503
Z_q	-0.0600	-0.0594	0.3911	0.6524
$Z_{\delta s}$	-0.0496	-0.0475	1.1131	1.4936
Z_o	0.0000	-0.0002	0.9742	1.4870
M_α	-0.6600	-0.6599	0.0086	0.0086
M_q	-0.1400	-0.1434	0.5610	0.7487
$M_{\delta s}$	-1.3265	-1.3175	0.6618	0.7779
M_o	0.0000	-0.0005	1.7136	1.7471
K_α	1.0000	1.0051	0.4151	0.4524
a_{z_o}	0.0000	-0.0008	1.0277	1.5639

Table 8 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 8 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1189	0.5204	0.6378
Z_q	-0.0600	-0.0608	0.5574	0.7960
$Z_{\delta s}$	-0.0496	-0.0534	2.0626	2.1984
Z_o	0.0000	0.0001	0.2962	0.6148
M_α	-0.6600	-0.6591	0.1022	0.1091
M_q	-0.1400	-0.1488	1.4299	1.5541
$M_{\delta s}$	-1.3265	-1.3376	0.8098	0.9708
M_o	0.0000	-0.0002	0.7846	1.2381
K_α	1.0000	0.9856	1.1581	1.3866
a_{z_o}	0.0000	0.0001	0.1900	0.3346

Table 9 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 9 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1176	1.1423	1.5923
Z_q	-0.0600	-0.0618	1.2403	2.3168
$Z_{\delta s}$	-0.0496	-0.0491	0.2888	0.3086
Z_o	0.0000	-0.0001	0.2937	0.6062
M_α	-0.6600	-0.6697	1.2030	1.2607
M_q	-0.1400	-0.1377	0.3846	0.6424
$M_{\delta s}$	-1.3265	-1.3222	0.3165	0.3578
M_o	0.0000	-0.0002	0.7802	1.0720
K_α	1.0000	0.9875	1.0244	1.4360
a_{z_o}	0.0000	-0.0002	0.3095	0.5527

Table 10 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 10 (white noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1196	0.1822	0.2446
Z_q	-0.0600	-0.0616	1.0827	1.6376
$Z_{\delta s}$	-0.0496	-0.0516	1.0752	1.4153
Z_o	0.0000	0.0000	0.1337	0.3304
M_α	-0.6600	-0.6582	0.2270	0.3590
M_q	-0.1400	-0.1324	1.2841	1.6340
$M_{\delta s}$	-1.3265	-1.3196	0.5162	0.6758
M_o	0.0000	0.0001	0.3587	0.7559
K_α	1.0000	1.0001	0.0083	0.0098
a_{z_o}	0.0000	0.0006	0.7700	1.5711

Table 11 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 11 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1149	2.8625	0.5850
Z_q	-0.0600	-0.0619	1.4836	0.3219
$Z_{\delta s}$	-0.0496	-0.0682	12.367	1.5388
Z_o	0.0000	-0.0012	5.1209	1.5395
M_{α}	-0.6600	-0.7419	12.371	2.3583
M_q	-0.1400	-0.0890	11.658	2.6873
$M_{\delta s}$	-1.3265	-1.2245	8.6593	1.6371
M_o	0.0000	-0.0029	10.913	2.2833
K_{α}	1.0000	0.8941	10.887	2.4662
a_{z_o}	0.0000	0.0022	3.4780	0.7790

Table 12 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 12 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.0994	13.290	2.6056
Z_q	-0.0600	-0.0707	9.8702	2.0558
$Z_{\delta s}$	-0.0496	-0.0544	3.7855	0.5116
Z_o	0.0000	0.0006	2.6205	0.5521
M_{α}	-0.6600	-0.6357	3.1622	0.5429
M_q	-0.1400	-0.2010	10.054	1.8170
$M_{\delta s}$	-1.3265	-1.4017	5.7487	1.0385
M_o	0.0000	-0.0013	4.4388	0.9535
K_{α}	1.0000	0.9231	6.7654	1.4972
a_{z_o}	0.0000	0.0025	4.3671	1.0023

Table 13 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 13 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1099	5.1625	0.9119
Z_q	-0.0600	-0.0621	1.4541	0.2987
$Z_{\delta s}$	-0.0496	-0.0699	11.311	1.8446
Z_o	0.0000	0.0033	16.282	1.9158
M_α	-0.6600	-0.5983	8.099	1.3766
M_q	-0.1400	-0.1512	1.9002	0.3340
$M_{\delta s}$	-1.3265	-1.3681	3.6237	0.5943
M_o	0.0000	0.0003	1.2479	0.2248
K_α	1.0000	0.8803	12.575	2.4115
a_{z_o}	0.0000	0.0008	1.0877	0.2456

Table 14 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 14 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1081	8.3870	1.3979
Z_q	-0.0600	-0.0731	12.996	2.3744
$Z_{\delta s}$	-0.0496	-0.0615	9.1655	1.2917
Z_o	0.0000	0.0000	0.1282	0.0286
M_α	-0.6600	-0.5681	17.640	2.6978
M_q	-0.1400	-0.1354	0.9946	0.1601
$M_{\delta s}$	-1.3265	-1.5225	19.407	2.6978
M_o	0.0000	0.0024	12.510	2.0434
K_α	1.0000	0.9276	8.2949	1.3658
a_{z_o}	0.0000	-0.0050	9.2577	1.8631

Table 15 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 15 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1045	8.3263	1.6232
Z_q	-0.0600	-0.0679	5.7664	1.4616
$Z_{\delta s}$	-0.0496	-0.0598	5.8118	1.0155
Z_o	0.0000	0.0014	6.5776	0.7742
M_α	-0.6600	-0.5980	8.3445	1.3884
M_q	-0.1400	-0.1786	6.7034	1.1026
$M_{\delta s}$	-1.3265	-1.4396	9.5540	1.5099
M_o	0.0000	-0.0014	5.5733	0.9312
K_α	1.0000	0.8851	11.832	2.3743
a_{z_o}	0.0000	-0.0039	5.3693	1.1936

Table 16 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 16 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1124	4.6543	0.9482
Z_q	-0.0600	-0.0563	3.3345	0.7702
$Z_{\delta s}$	-0.0496	-0.0610	7.9378	1.0951
Z_o	0.0000	0.0017	7.5169	2.6730
M_α	-0.6600	-0.6657	0.8029	0.1566
M_q	-0.1400	-0.1300	1.9607	0.4864
$M_{\delta s}$	-1.3265	-1.3777	4.2624	0.8354
M_o	0.0000	-0.0032	11.224	2.3899
K_α	1.0000	0.8907	10.786	2.7068
a_{z_o}	0.0000	0.0010	1.5965	0.3650

Table 17 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 17 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1330	6.1532	1.2228
Z_q	-0.0600	-0.0559	2.8302	0.6600
$Z_{\delta s}$	-0.0496	-0.0446	2.8864	0.4214
Z_o	0.0000	-0.0008	3.1786	0.7223
M_α	-0.6600	-0.6674	0.9175	0.1392
M_q	-0.1400	-0.1669	4.3509	0.6964
$M_{\delta s}$	-1.3265	-1.3144	0.9017	0.1410
M_o	0.0000	0.0006	2.1354	0.4174
K_α	1.0000	0.9871	1.0957	0.2132
a_{z_o}	0.0000	-0.0063	8.9763	2.1863

Table 18 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 18 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1258	3.3745	0.7023
Z_q	-0.0600	-0.0616	1.4015	0.3568
$Z_{\delta s}$	-0.0496	-0.0394	7.2608	1.3276
Z_o	0.0000	-0.0004	1.8180	0.3257
M_α	-0.6600	-0.7327	9.6633	1.4463
M_q	-0.1400	-0.1669	5.2334	1.0887
$M_{\delta s}$	-1.3265	-1.2966	2.4478	0.4103
M_o	0.0000	-0.0027	9.9423	1.6606
K_α	1.0000	1.0656	5.7806	1.1744
a_{z_o}	0.0000	0.0009	1.5384	0.3534

Table 19 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 19 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1087	6.2247	1.0573
Z_q	-0.0600	-0.0721	9.2315	1.5896
$Z_{\delta s}$	-0.0496	-0.0751	16.660	2.1714
Z_o	0.0000	-0.0007	3.0161	0.9104
M_{α}	-0.6600	-0.6194	5.2636	0.7920
M_q	-0.1400	-0.2087	10.602	2.0165
$M_{\delta s}$	-1.3265	-1.4105	6.1350	0.9313
M_o	0.0000	0.0009	3.5568	0.6639
K_{α}	1.0000	0.9515	4.3324	0.7987
a_{z_o}	0.0000	0.0016	2.5690	0.5834

Table 20 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 20 (band limited noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1383	8.2762	1.6074
Z_q	-0.0600	-0.0738	8.8645	1.6306
$Z_{\delta s}$	-0.0496	-0.0535	2.2699	0.3648
Z_o	0.0000	-0.0010	4.7563	0.9479
M_{α}	-0.6600	-0.6931	4.7258	0.9052
M_q	-0.1400	-0.1183	4.2280	0.8128
$M_{\delta s}$	-1.3265	-1.1958	11.693	2.5125
M_o	0.0000	0.0016	7.6997	1.8215
K_{α}	1.0000	1.1679	13.186	3.2653
a_{z_o}	0.0000	0.0050	7.6176	1.9777

Table 21 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 21 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1061	7.5168	1.3607
Z_q	-0.0600	-0.0533	4.9643	1.1594
$Z_{\delta s}$	-0.0496	-0.0545	2.6371	0.4190
Z_o	0.0000	0.0011	4.7742	1.4312
M_{α}	-0.6600	-0.6146	5.6133	0.9139
M_q	-0.1400	-0.2056	10.611	1.8809
$M_{\delta s}$	-1.3265	-1.5247	14.548	2.2400
M_o	0.0000	-0.0003	1.1757	0.2369
K_{α}	1.0000	0.8501	15.686	3.2294
a_{z_o}	0.0000	0.0051	6.8756	1.6655

Table 22 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 22 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.0980	12.151	2.4711
Z_q	-0.0600	-0.0596	0.3084	0.0843
$Z_{\delta s}$	-0.0496	-0.0727	13.159	2.3480
Z_o	0.0000	0.0025	11.567	2.1292
M_{α}	-0.6600	-0.6460	1.9121	0.2917
M_q	-0.1400	-0.1039	7.1132	1.2110
$M_{\delta s}$	-1.3265	-1.3936	5.6630	0.9275
M_o	0.0000	-0.0001	0.3830	0.0599
K_{α}	1.0000	0.8992	9.6421	1.7422
a_{z_o}	0.0000	0.0031	4.4546	1.0164

Table 23 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 23 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1392	9.4275	1.8622
Z_q	-0.0600	-0.0618	1.3040	0.3227
$Z_{\delta s}$	-0.0496	-0.0379	7.2643	1.1618
Z_o	0.0000	0.0016	8.0830	1.0965
M_α	-0.6600	-0.8052	19.129	2.9224
M_q	-0.1400	-0.0535	20.405	3.1831
$M_{\delta s}$	-1.3265	-1.1171	18.589	2.9508
M_o	0.0000	-0.0036	13.580	2.0105
K_α	1.0000	1.1461	12.255	1.8967
a_{z_o}	0.0000	-0.0114	16.743	3.4106

Table 24 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 24 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1027	9.8009	2.0916
Z_q	-0.0600	-0.0704	8.1676	2.1834
$Z_{\delta s}$	-0.0496	-0.0603	6.5715	1.2755
Z_o	0.0000	0.0019	8.7375	2.8303
M_α	-0.6600	-0.6089	6.6303	1.1690
M_q	-0.1400	-0.1711	5.1944	0.9892
$M_{\delta s}$	-1.3265	-1.4595	10.420	1.7979
M_o	0.0000	0.0025	10.118	1.9189
K_α	1.0000	0.9955	0.3821	0.0893
a_{z_o}	0.0000	0.0066	10.434	2.7255

Table 25 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 25 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1257	3.0188	0.5376
Z_q	-0.0600	-0.0580	1.5276	0.2589
$Z_{\delta s}$	-0.0496	-0.0407	5.3341	0.7403
Z_o	0.0000	-0.0017	7.3544	1.5254
M_α	-0.6600	-0.5431	16.323	2.9242
M_q	-0.1400	-0.2109	10.844	1.7878
$M_{\delta s}$	-1.3265	-1.5004	13.443	2.2870
M_o	0.0000	0.0028	12.062	2.2904
K_α	1.0000	0.9085	8.8839	1.5744
a_{z_o}	0.0000	-0.0061	8.8680	2.0119

Table 26 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 26 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1403	10.344	2.1157
Z_q	-0.0600	-0.0491	8.6461	2.2289
$Z_{\delta s}$	-0.0496	-0.0293	13.587	3.2656
Z_o	0.0000	-0.0027	10.554	2.8641
M_α	-0.6600	-0.6383	3.0224	0.4923
M_q	-0.1400	-0.1871	7.5879	1.2408
$M_{\delta s}$	-1.3265	-1.3930	4.7080	0.7781
M_o	0.0000	0.0023	9.1923	1.5604
K_α	1.0000	1.0088	0.7208	0.1160
a_{z_o}	0.0000	-0.0060	9.4544	2.1602

Table 27 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 27 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1282	3.8259	0.7433
Z_q	-0.0600	-0.0637	2.4450	0.4965
$Z_{\delta s}$	-0.0496	-0.0569	4.3716	0.6075
Z_ρ	0.0000	-0.0021	8.9336	2.8628
M_α	-0.6600	-0.5912	8.7992	1.5334
M_q	-0.1400	-0.2033	9.2512	1.7920
$M_{\delta s}$	-1.3265	-1.3229	0.2754	0.0477
M_ρ	0.0000	0.0005	2.1958	0.4992
K_α	1.0000	1.0787	6.0239	1.1390
a_{z_0}	0.0000	-0.0062	8.7125	2.1701

Table 28 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 28 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{ \hat{\theta} - \theta }{\text{standard } \sigma}$	$\frac{ \hat{\theta} - \theta }{\text{corrected } \sigma}$
Z_α	-0.1200	-0.1018	9.7989	1.8491
Z_q	-0.0600	-0.0602	0.1275	0.0231
$Z_{\delta s}$	-0.0496	-0.0709	13.386	1.9596
Z_ρ	0.0000	0.0010	3.8657	1.4456
M_α	-0.6600	-0.6244	4.7377	0.8179
M_q	-0.1400	-0.1187	3.5376	0.7562
$M_{\delta s}$	-1.3265	-1.3361	0.7291	0.1450
M_ρ	0.0000	-0.0017	5.9438	1.4466
K_α	1.0000	0.8465	13.959	3.0485
a_{z_0}	0.0000	-0.0005	0.7315	0.1856

Table 29 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 29 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1053	7.9948	1.1955
Z_q	-0.0600	-0.0527	5.4278	1.5089
$Z_{\delta s}$	-0.0496	-0.0594	5.4603	0.9909
Z_o	0.0000	0.0022	10.157	1.7000
M_{α}	-0.6600	-0.6366	3.5389	0.6381
M_q	-0.1400	-0.1020	7.6247	1.4104
$M_{\delta s}$	-1.3265	-1.3994	6.0895	1.1411
M_o	0.0000	0.0015	6.6273	1.2007
K_{α}	1.0000	0.9739	2.5720	0.4449
a_{z_v}	0.0000	0.0035	5.1899	1.0830

Table 30 LONGITUDINAL DYNAMIC MODEL PARAMETER ESTIMATES AND
CRAMER-RAO BOUNDS - RUN 30 (colored noise)

Parameter	True Value, θ	Estimate, $\hat{\theta}$	$\frac{\hat{\theta} - \theta}{\text{standard } \sigma}$	$\frac{\hat{\theta} - \theta}{\text{corrected } \sigma}$
Z_{α}	-0.1200	-0.1303	4.8615	0.8891
Z_q	-0.0600	-0.0619	1.2497	0.3016
$Z_{\delta s}$	-0.0496	-0.0602	6.0041	0.9943
Z_o	0.0000	-0.0012	5.3350	1.0467
M_{α}	-0.6600	-0.7208	8.0705	1.2027
M_q	-0.1400	-0.1472	1.3693	0.2678
$M_{\delta s}$	-1.3265	-1.2376	7.3530	1.2539
M_o	0.0000	-0.0051	18.109	2.6469
K_{α}	1.0000	0.9600	3.8148	0.7254
a_{z_v}	0.0000	-0.0026	3.2722	0.6512

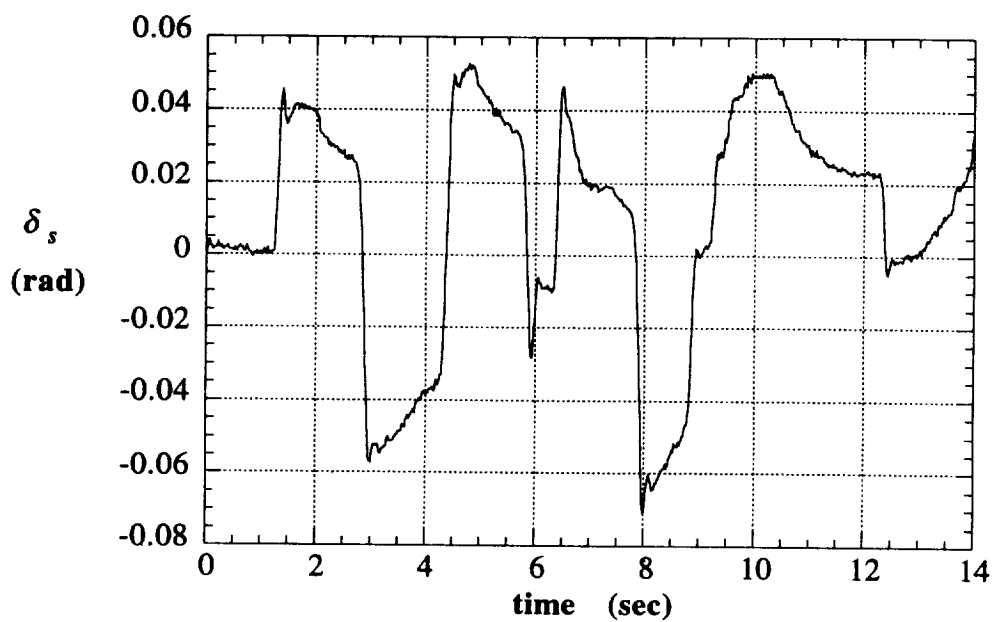


Figure 1 Stabilator input

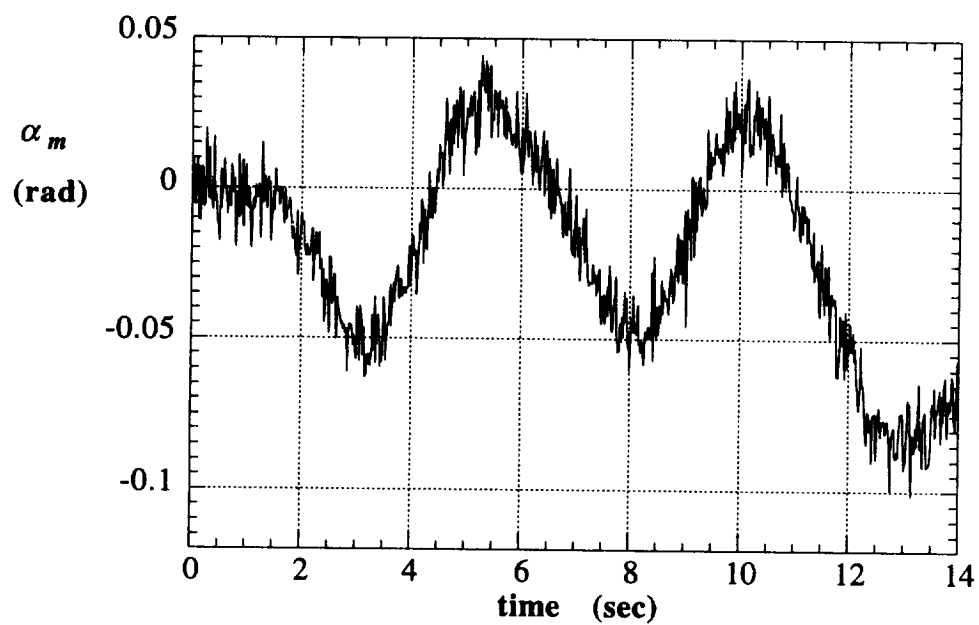


Figure 2(a) Simulated angle of attack with white measurement noise

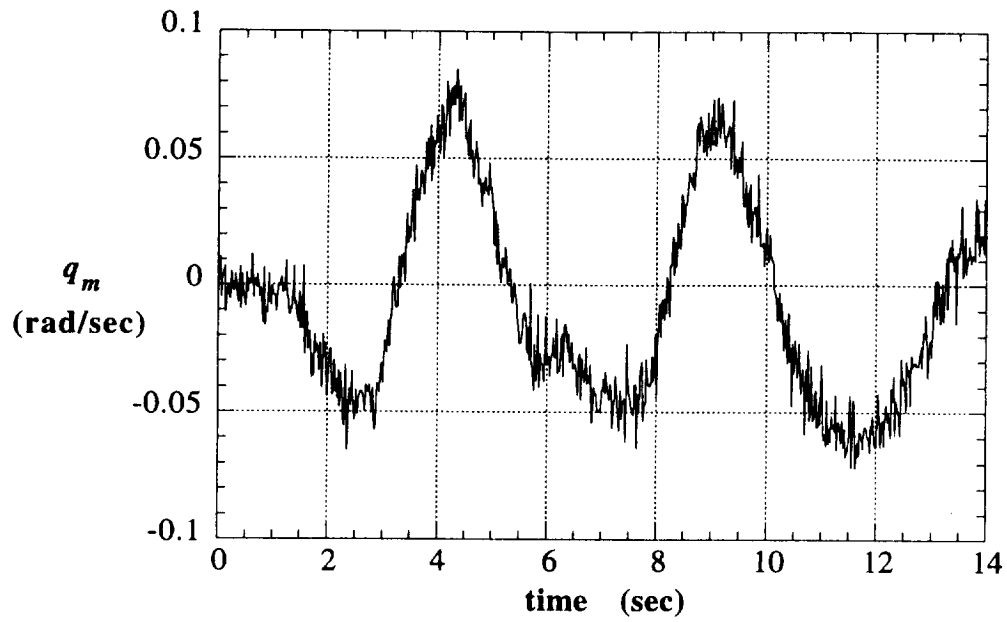


Figure 2(b) Simulated pitch rate with white measurement noise

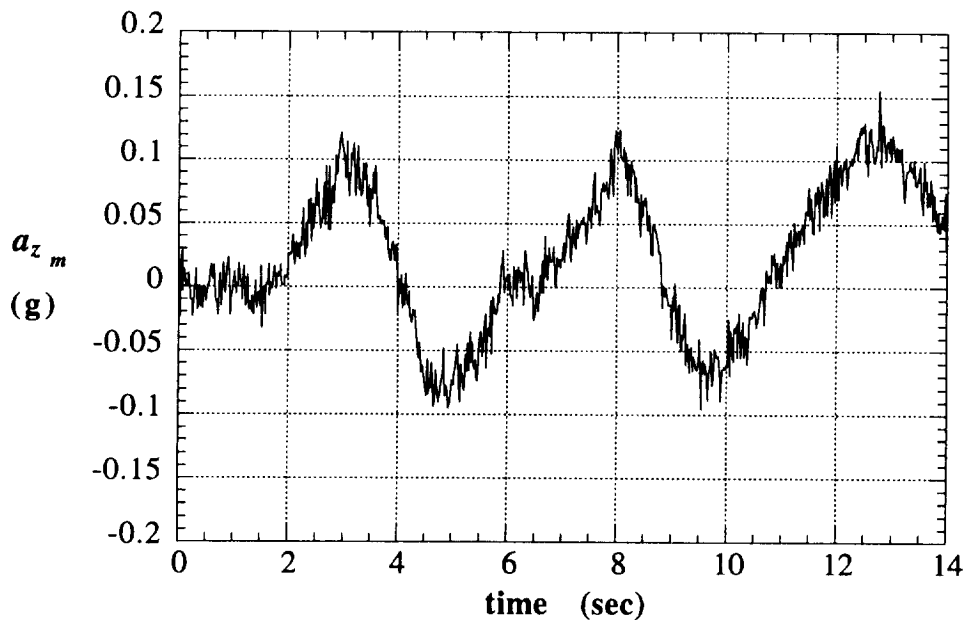


Figure 2(c) Simulated vertical acceleration with white measurement noise

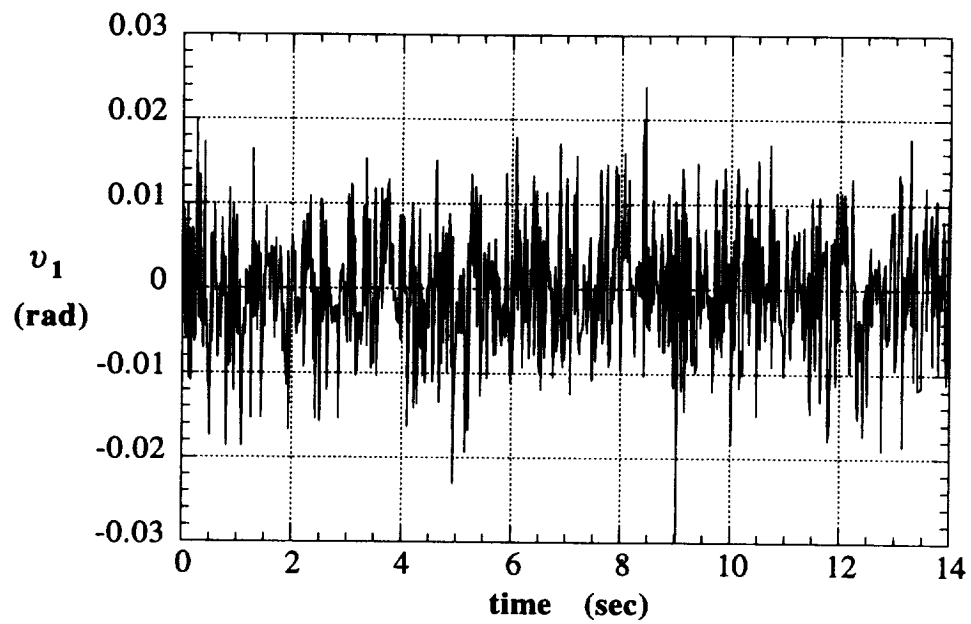


Figure 3 White noise sequence added to angle of attack

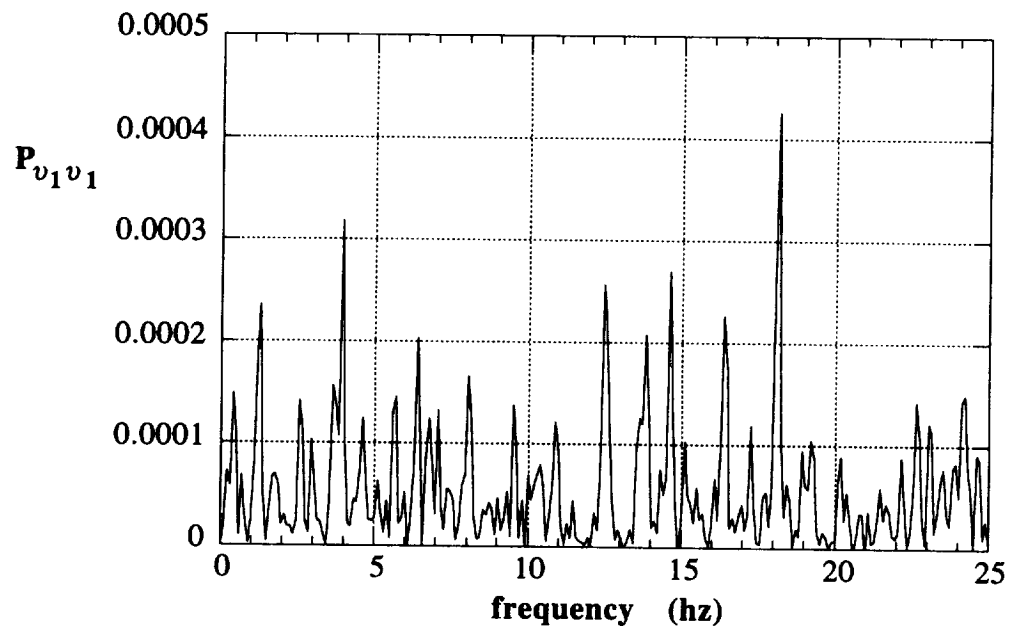


Figure 4 Power spectrum of white noise added to angle of attack

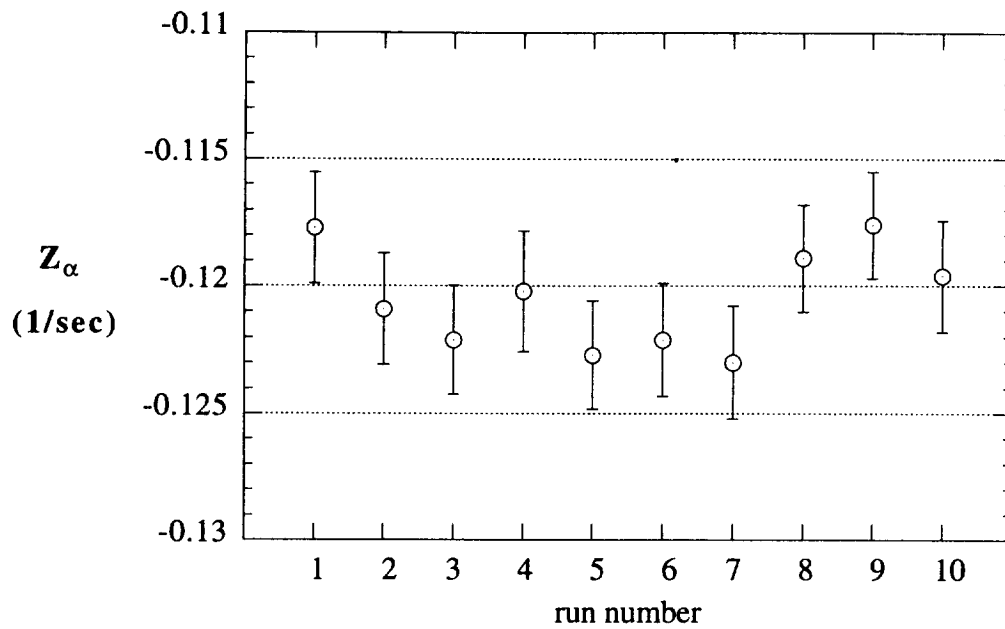


Figure 5 Z_α parameter estimates with standard Cramer-Rao bounds for white noise

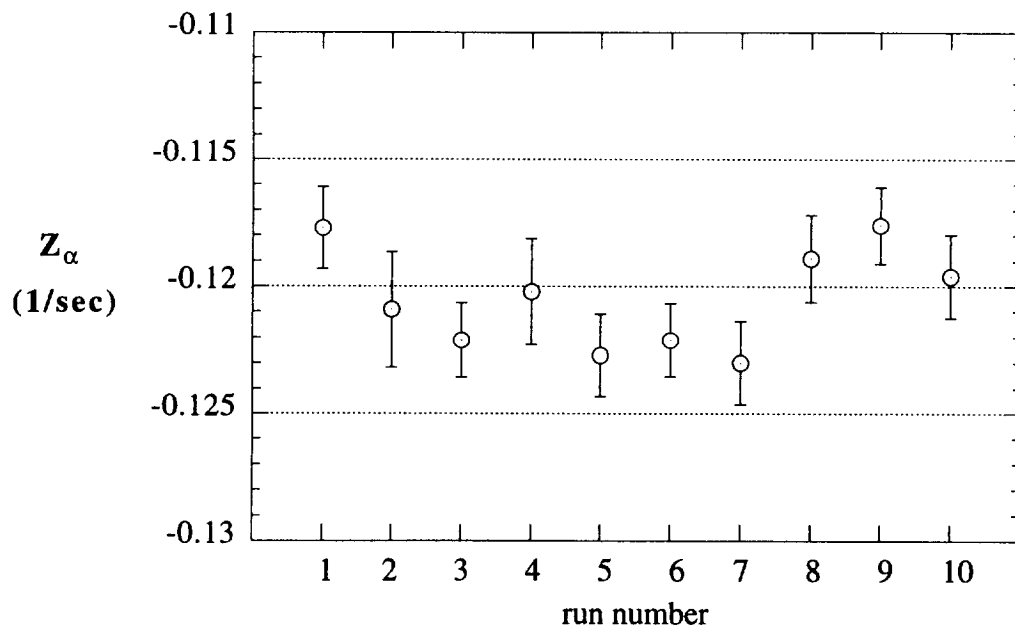


Figure 6 Z_α parameter estimates with corrected Cramer-Rao bounds for white noise

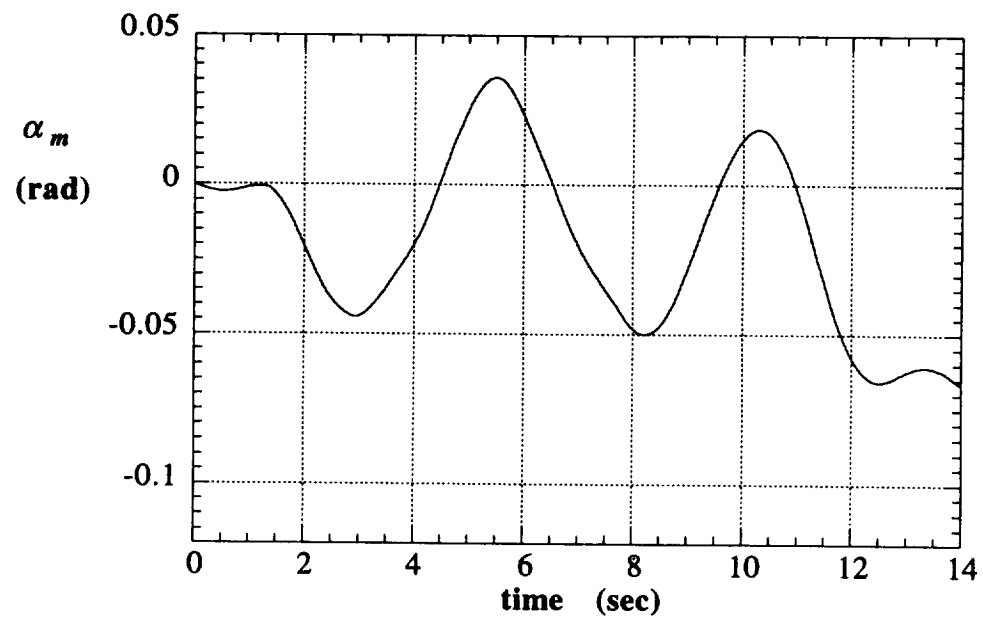


Figure 7(a) Simulated angle of attack with band limited measurement noise

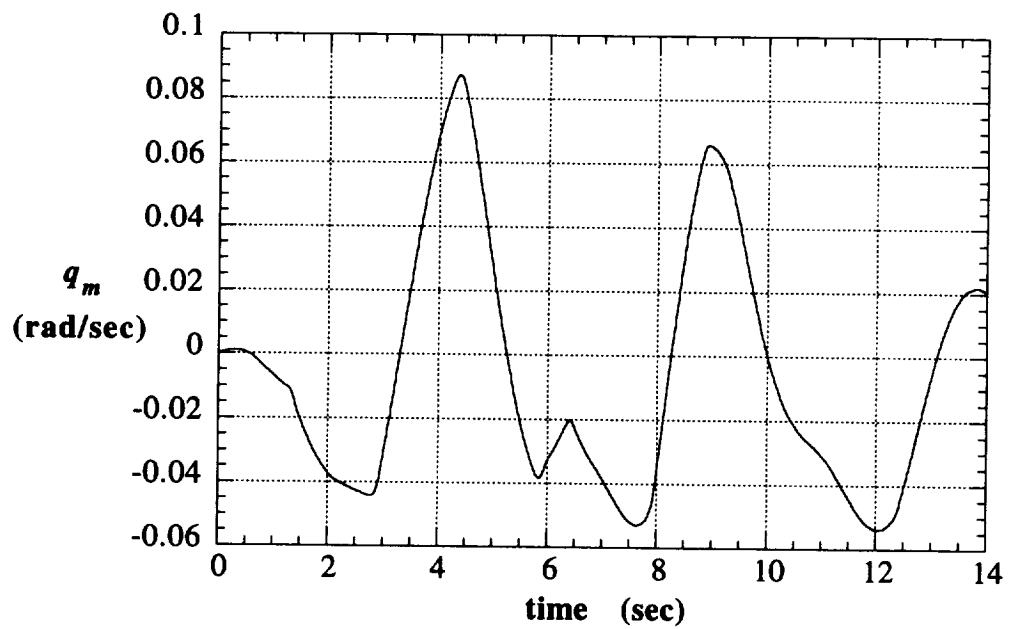


Figure 7(b) Simulated pitch rate with band limited measurement noise

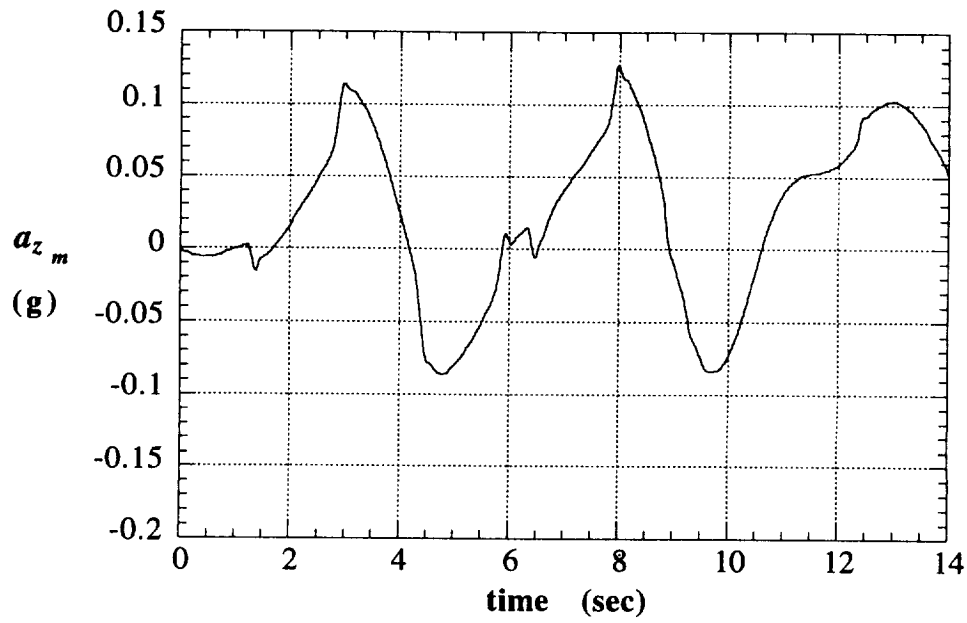


Figure 7(c) Simulated vertical acceleration with band limited measurement noise

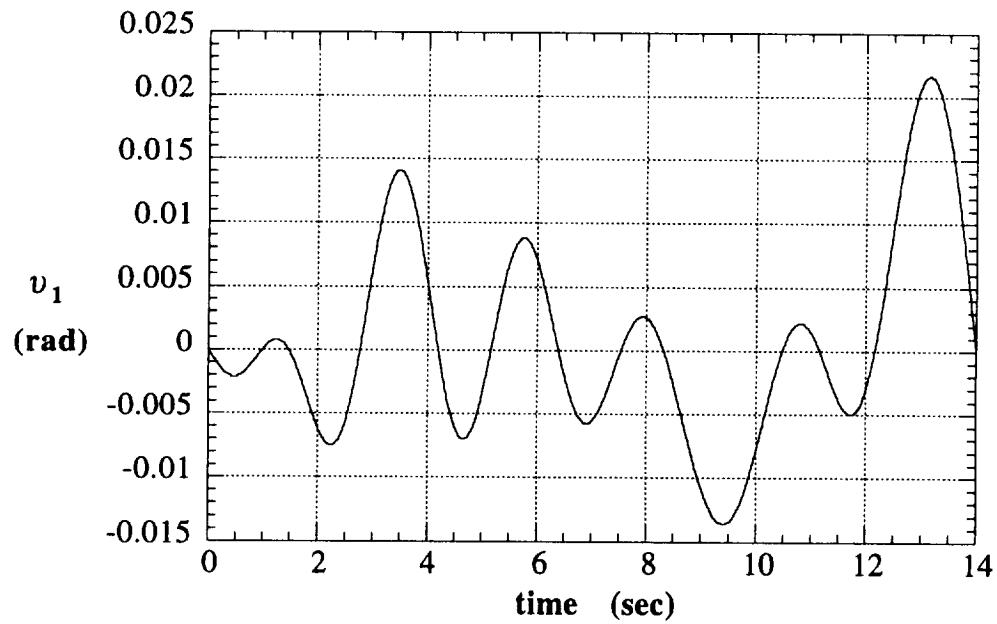


Figure 8 Band limited noise sequence added to angle of attack

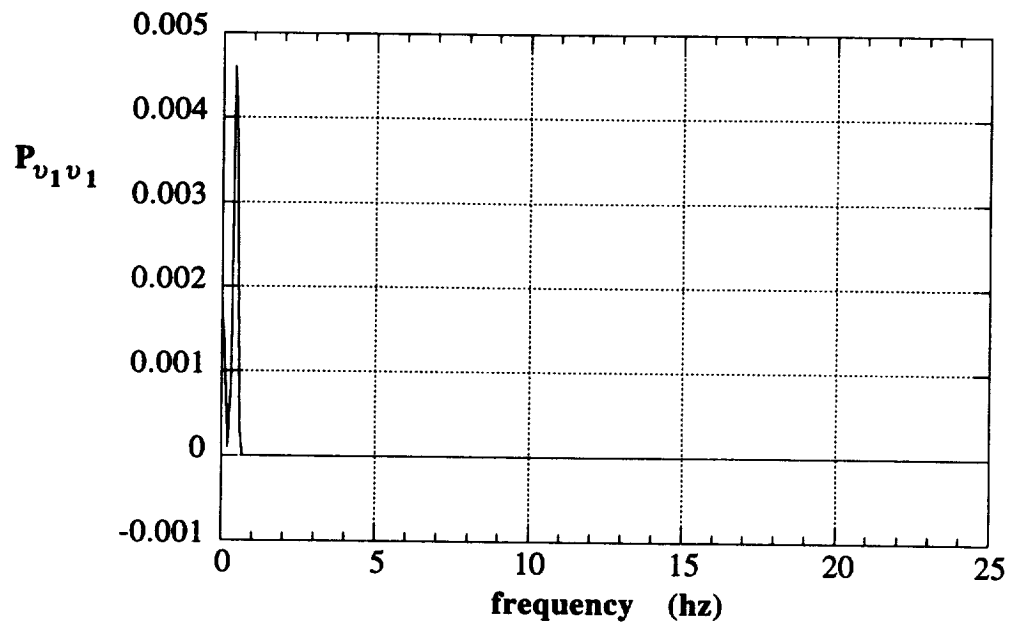


Figure 9 Power spectrum of band limited noise added to angle of attack

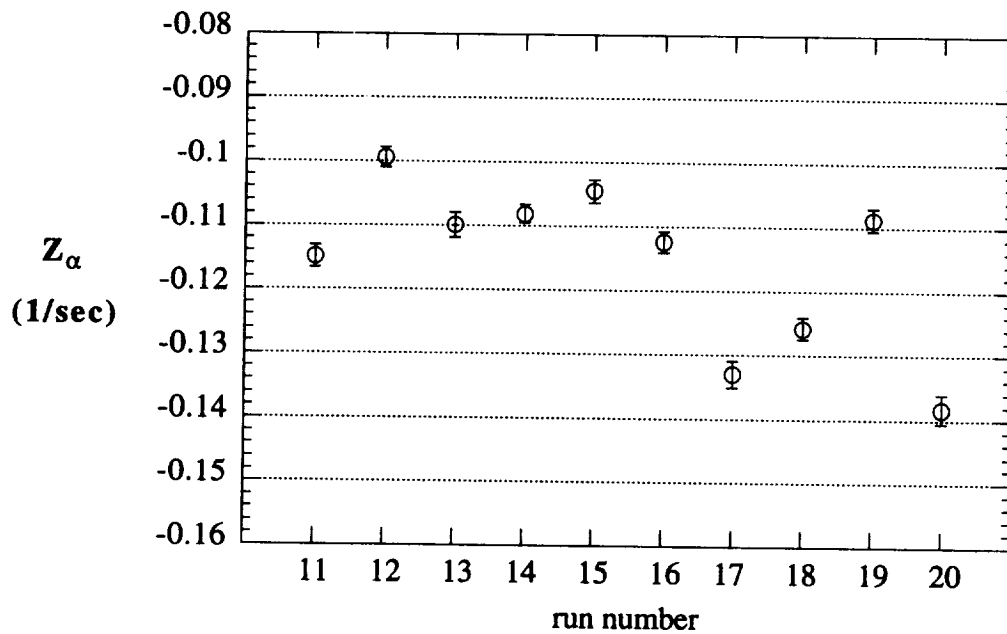


Figure 10 Z_{α} parameter estimates with standard Cramer-Rao bounds for band limited noise

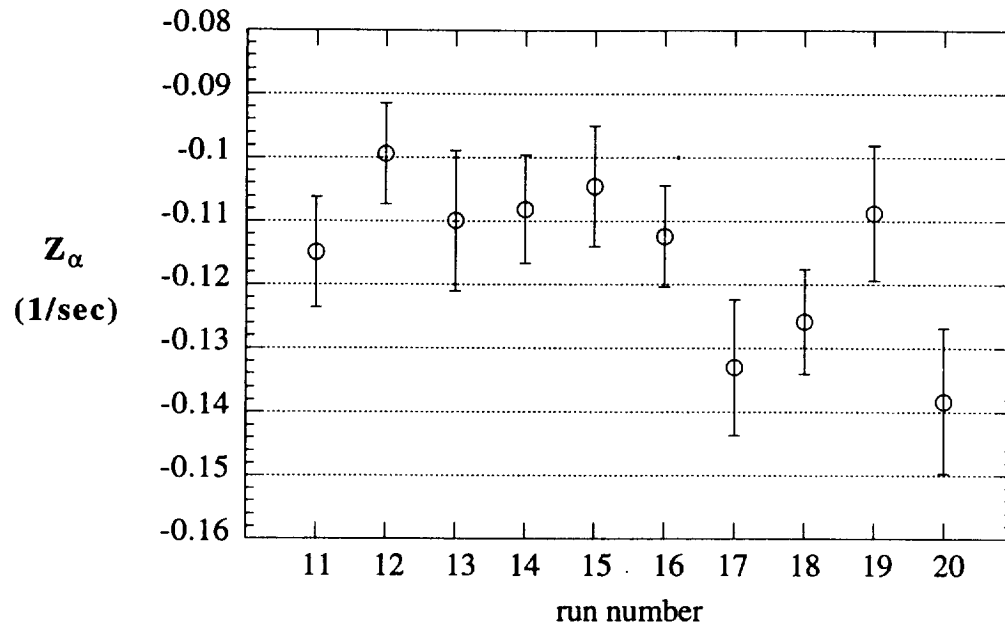


Figure 11 Z_α parameter estimates with corrected Cramer-Rao bounds for band limited noise

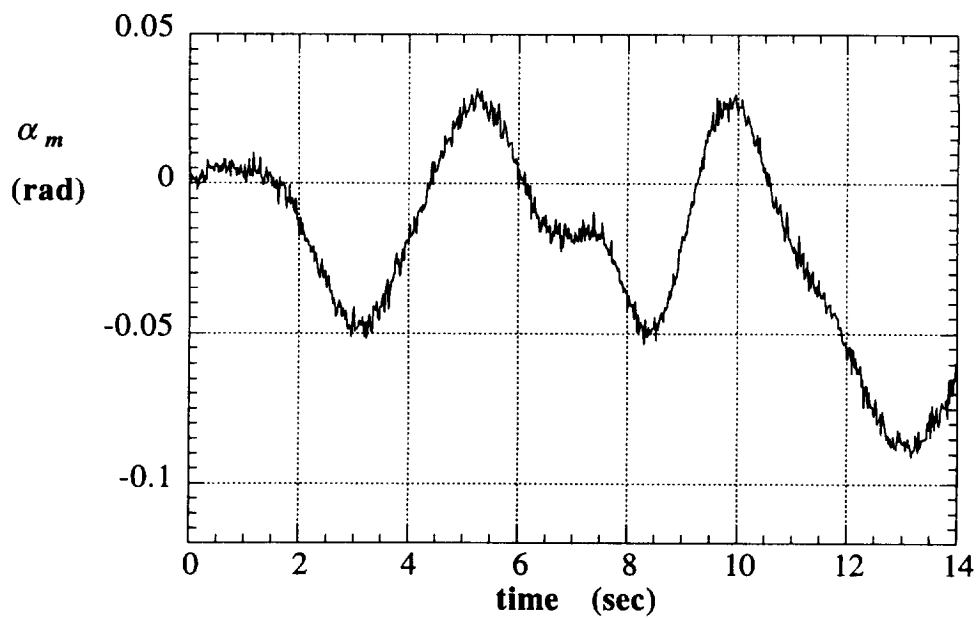


Figure 12(a) Simulated angle of attack with colored measurement noise

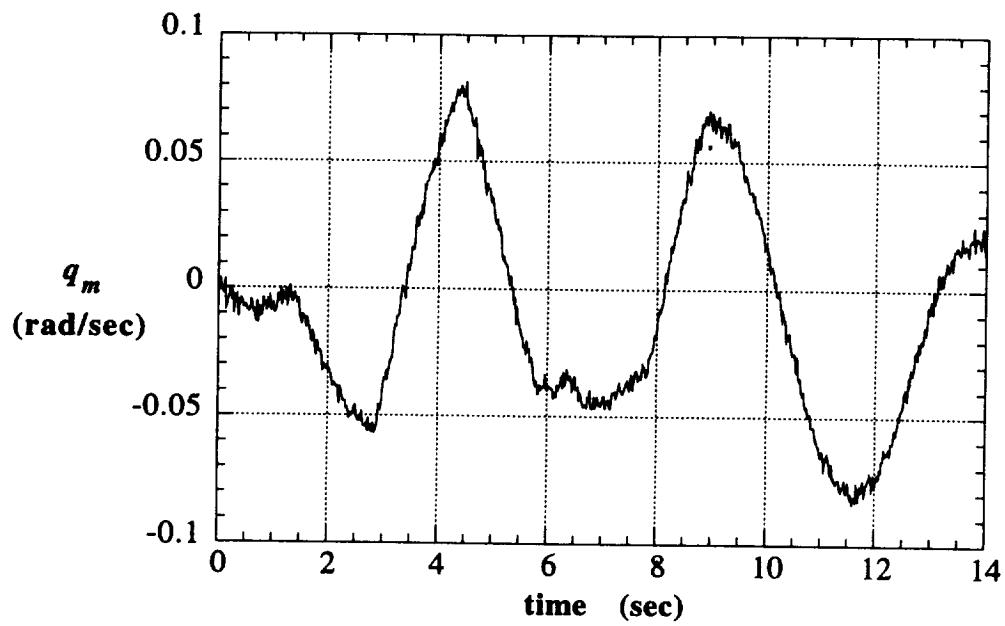


Figure 12(b) Simulated pitch rate with colored measurement noise

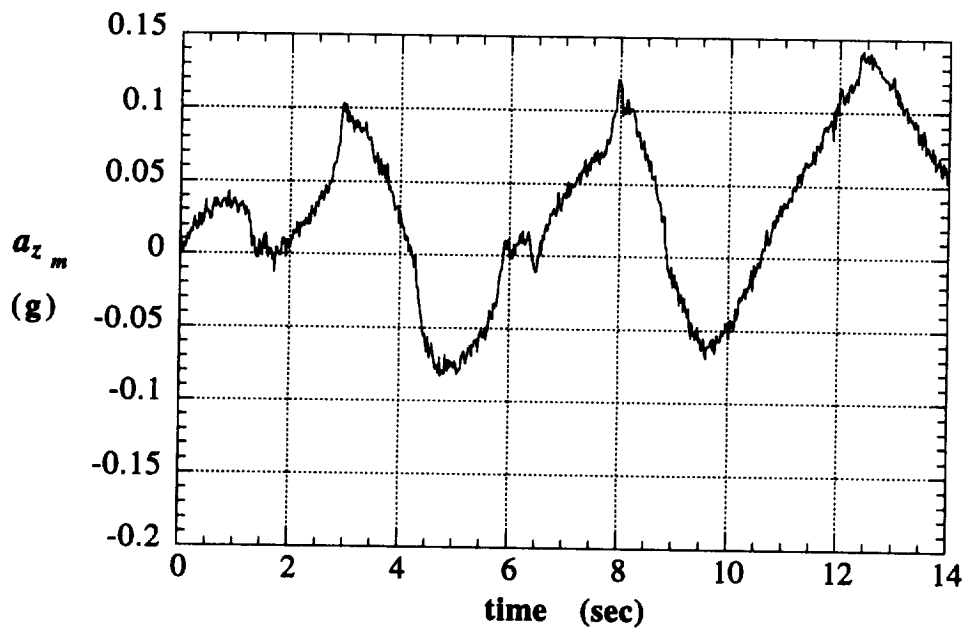


Figure 12(c) Simulated vertical acceleration with colored measurement noise

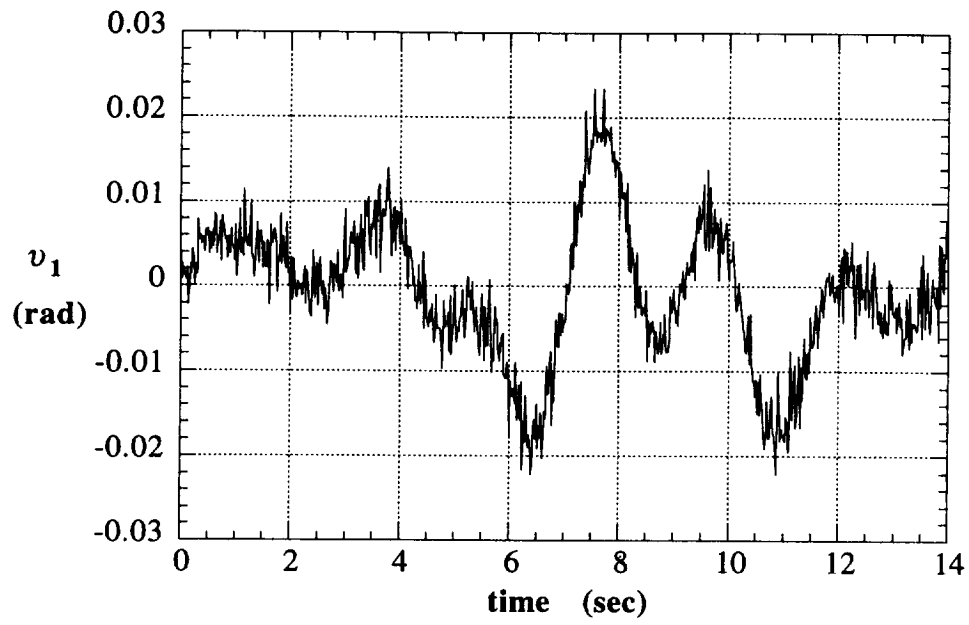


Figure 13 Colored noise sequence added to angle of attack

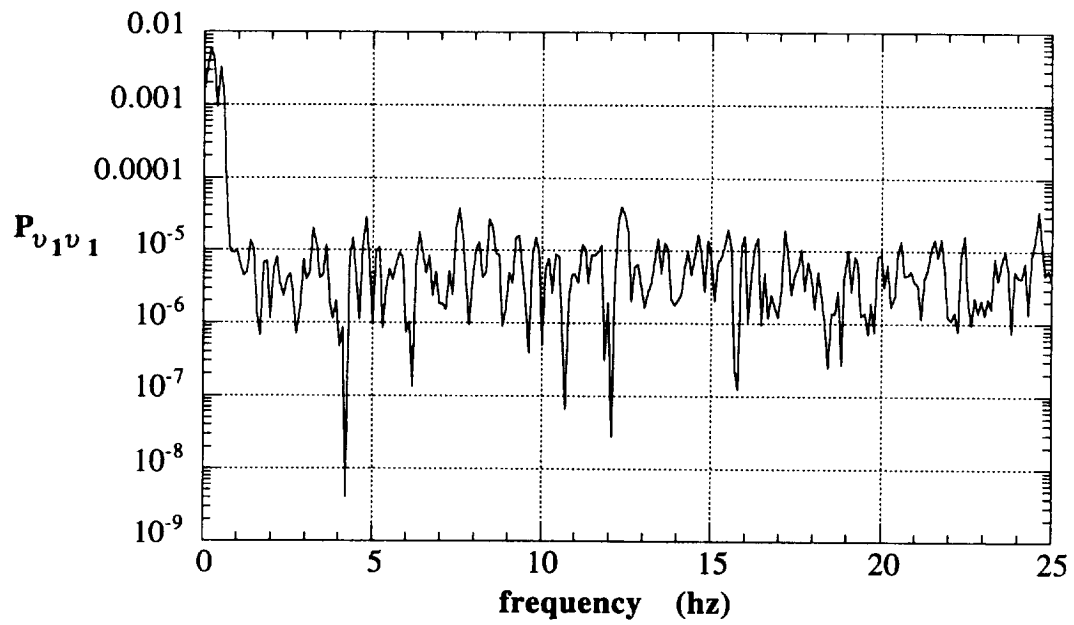


Figure 14 Power spectrum of colored noise added to angle of attack

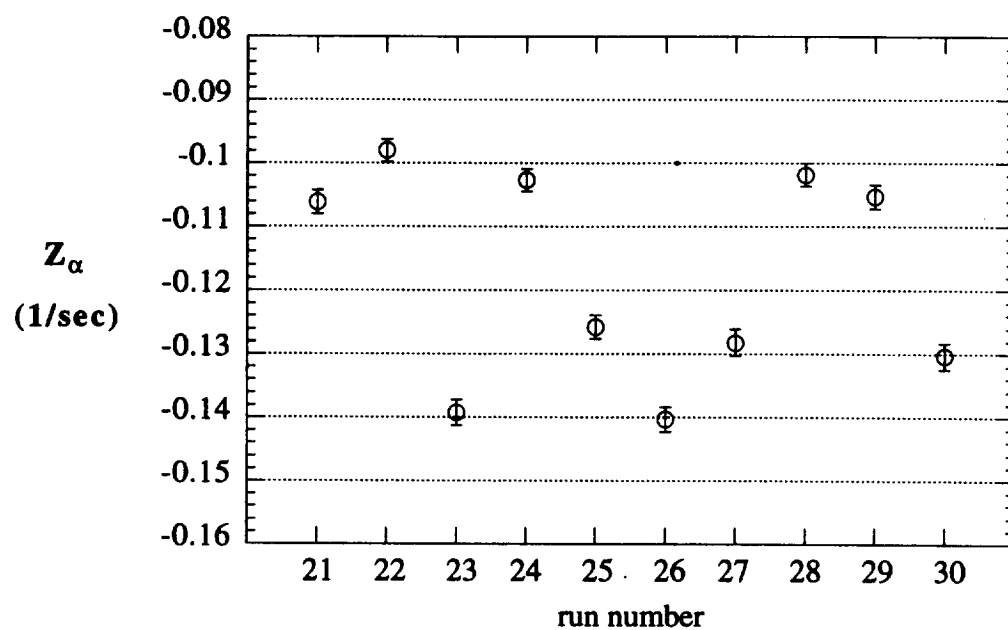


Figure 15 Z_α parameter estimates with standard Cramer-Rao bounds for colored noise

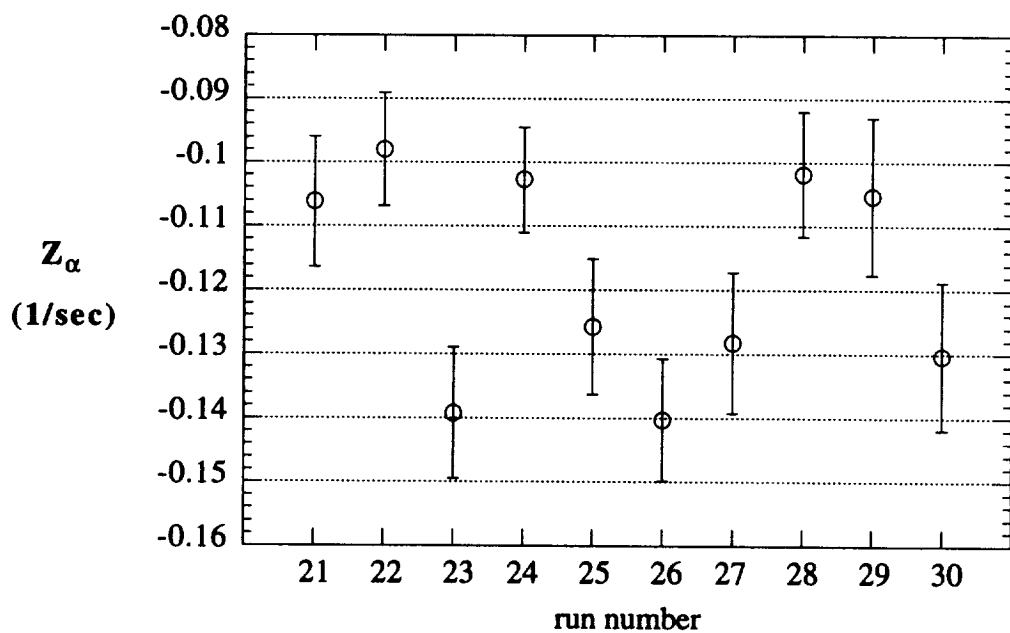


Figure 16 Z_α parameter estimates with corrected Cramer-Rao bounds for colored noise

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